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Driver State Monitoring Systems– Transferable knowledge manual driving to HAD

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Abstract

Highly Automated Driving (HAD) will be commercially available in a near feature, yet human factors issues like the influence of driver state can have a critical impact in the success of this driving paradigm and also in road safety. It is very likely that Driver State Monitoring Systems (DSMS) will play a bigger role than they have played so far. However with this new driving paradigm shift is important to select highlight what is transferable from the previous systems. Due to lack of driving task engagement, driving performance metrics are no longer viable, creating opportunities for other approaches like detecting non-driving task engagement or fatigue countering behaviours. Eye based metrics will remain important.

Keywords: Driver state; Driver State Monitor; Human factors; Highly automated driving; Driver impariment

1. Introduction

Human Factors in AUTOmated driving (HFAuto) is an European project aiming to clarify the impact human factors has on Highly Automated Driving (HAD). According to BASt definition [1], in HAD an automated driver controls the vehicle's longitudinal and lateral control, while the human driver is only required to resume control if the vehicle requests due to system limitations. The novelty of this concept is that it assumes the driver is engaged on non-related driving tasks and does not enforce supervision, creating a significant different driving experience.

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Vehicle control transition plays a critical role for the success of HAD, due to the new human role in this paradigm. Ideally, the human driver is paying attention to the driving scene and is ready to intervene in case of a Take Over Request (TOR). However, HAD concept heads in a direction where drivers are allowed to be in distracted, inattentive, or even fatigue status. Under similar driving scenario and automation behaviour, a driver with some sort of impairment will have poorer performance handling the situation than if s/he was in the ideal state. For instance, in [2] Merat et al shows distracted HAD drivers to have higher difficulty to adjust speed to a critical event than attentive drivers. Also, [3] Saxby et al perform an experiment where groups experiencing active fatigue, and passive fatigue in a automated vehicle would perform different to emergency event. While automation behaviour can be fairly standardized and therefore predict the outcome, the human behaviour/performance is conditioned by their state. This unpredictability can compromise TOR processes, jeopardizing a driving concept that tries to minimize the intervention [4] from the major responsible for accidents [5], the human driver.

1.1. Driver State Monitoring Systems

Driver State Monitoring Systems (DSM), in its essence, are systems that collect observable information about the human driver in order to assess driver's capability to perform the driving task in a safe manner. DSM concept is often addressed in other terms like: DIM (Driver Impairment Monitor [6]), DIMS (Driver Inattention Monitor Systems) used in [7], and is more generic than Driver Vigilance Monitoring (VDM) from [8]. Applications of this technology can be used for active safety, adaptive Human Machine Interface (HMI), and annoyance reduction for false positive notifications [9]. With the arrival of HAD, these systems gained more relevance due to the need for understanding and adjusting to the driver conditions. Unfortunately, DSMS has been mainly isolated systems, custom designed for single purpose application such as distraction detection [9]–[12] or drowsiness detection systems [13]–[15].

The major contribution of this paper is to provide an overview on DSM from a HAD point of view. There are several DSM reviews available [7], [14], [16], but none of these aims to transfer this knowledge to HAD context. Furthermore, we also point some directions DSM systems need to take in order to meet HAD requirements.

1.2. Driver state

There is no universal definition of what is considered driver state, actually the term is often used in a loosely manner from psychologists and engineers communities. In general, driver state refers to a set of conditions that affect the driver in a specific instance. Drivers in an optimal state do not suffer from any condition. For this reason, DSMS are designed to host modules that identify specific conditions. These conditions fall into two main categories: distraction and fatigue [7]. These categories can also be considered equivalent to HAVEit's driver state attention and alertness components[17].

Note that there are other known conditions that do not fit in any of these categories. For example, intoxicated (alcohol or drugs) drivers have considerably more difficult to cope with the driving task. Although it is questionable if even in a HAD context drivers could be allowed to engage under such condition, its detection without driving performance (due to HAD) or blood analysis makes the diagnose impossible or very intrusive. For this same reason, forms of fatigue such as physical fatigue originated from exerting activities prior to the travel could also be hard to detect without heart rate or questionnaires. Therefore, we will only consider for the purpose of this review conditions whose diagnose technology depends on non-intrusive and direct measurement techniques.

2. Distraction

We consider distraction an attention shift away from driving related tasks, by allocating resources need for the driving task to non-driving tasks. Numerous factors endogenous and exogenous factors to the vehicle can happen (for exhaustive lists [18][19]). When distracted, the driver looses awareness of the current driving situation translating into vigilance decrements and higher collision risk. For this document we will consider the following distraction categories: visual, auditory, mechanical, and mental. These categories aim to represent the predominant resource being used, according to the multiple resource theory.

In Table 1are the most relevant head/eye based metrics obtained from eye-tracking systems. Visual distraction is usually associated to looking away from the road scene, for example read information from the In Vehicle Information System (IVIS). From the eye behaviour process, the gaze is the dominant subprocess used to detect distraction.

Eyes-Off-Road (EOF) duration is perhaps the most used metric detect distracted drivers, the higher the time the lower the driver's awareness due to its simplicity and effectiveness to check if the driver was actually looking to the road [20]. In studies where researchers create virtual areas of interest (AOI), then glance's space and time dimensions allow a more detailed analysis than the binary approach of eyes on/off the road. Glance Pattern refers to sequence of AOI fixated by the driver. AOI sequence allows predicting driver's intentions, for instance mirrors checking before overtaking another vehicle. Visual task engagement is also possible to detect, by comparing with normative pattern. Mean Glance Duration highlights the time spent on each AOI, which similar to the previous Glance Patter utility enables the detection of disproportional gaze time allocation as an indicator of task engagement/distraction.

Table 1. Set of metrics associated with distraction detection.

Type Distraction	Reference Metrics
Visual	Glance Pattern[21]
	Mean Glance Duration [22]
	Eyes-Off-Road Duration [23]
Auditory	Pupil Diameter[24]
	Blink Frequency[25]
Mechanical	Head direction[15]
Cognitive	Pupil Diameter[24]

Pupil Diameter has been reported to be sensitive to Cognitive (i.e. mind wandering) and for Auditory (i.e. reacting to cellphone ring). In [24], Tursky et al design an experiment with tasks and levels of difficulty. The pupil reacted consistently by allowing distinguishing between different task, and also the level of difficulty.

Mechanical distraction is related to the driver's body posture during the driving task. For instance, a driver facing the passenger seat reduces his vision of the road center and also is in a non-ideal position for resuming control of the car in the case of a sudden event. Head direction has been used in HAVEit as a variable to assess the driver distraction [15].

3. Fatigue

The Fatigue category includes the cases where human drivers are experience lack of motivation to engage in the driving task, instead they seek more confortable goals in order to rest. Like in vigilance tasks over relatively long periods, there is a natural vigilance decrement occurs however is also followed by drowsiness signs and perception of being tired. Fatigue is treated separately from other forms of inattention because: 1) it not only reduces situation awareness but also affects the central nervous system and consequently mental and motor coordination [26][27]; 2) has a higher temporal window associated with minutes or hours [17]. For a review on definitions of fatigue please consult [28].

For the purpose of this document, we focus on passive fatigue. This type of fatigue is characterized by being the indirect product of the human driver's exertion of a set of tasks whose demands are low, monotonous or repetitive[3]. This rules out any sort of physical fatigue or mental active fatigue.

In Table 2 we present a list of metrics commonly used for detecting fatigue. The eye based signals are useful because exists a deep nervous connection between the brain and eye [27]. These motor and sensor connections between both organs allow monitoring signals associated to fatigue that are not controlled consciously by the human. With the progress in image processing systems and camera technology, today is quite common to use eye-tracking systems for obtaining many reliable metrics.

Table 2. Set of measurements associated with fatigue detection.

Type Metrics	Metrics
Eye Based	PERCLOS[29][30][31]
	EYEMEAS [29]
	MEANCLOS[29]
	AECS[29]
	Blink Frequency[29]
	Microsleep rate[29]
Behaviour Based	Yawning [31]
	Nodding [29]
	Slouching[32]
	Eyebrow rising[33]

While distraction eye based metrics are focused on the gaze process, fatigue metrics rely on the eye-lid movement process. By observing the blinking behaviour [25], [29] increments in frequency can be associated with reduced vigilance [25]. Blink metrics are usually defined with a minimum time acceptance (bellow the blinks are ignored due to noise data) and a maximum time from which is already considered a Microsleep. Microsleeps are inherently associated to fatigue so in this case also the increase represents a degradation of the fatigue condition. EYEMEAS (Mean Square Eye Closure), MEANCLOS (Mean Eye Closure), and AECS (Average Eye Closure Speed) metrics use raw eyelid behaviour over medium size time intervals, providing an overview of that interval. The most used metric is the PERCLOS (Percentage Eye Closure) present in projects from academia to commercial applications [34].

Eye metrics value is unquestionable due to the ability to obtain relevant data associated with fatigue in a non-intrusive way, and also enjoys a broad community acceptance. However, eye metrics also have considerable drawbacks. First, despite the progress in camera technology, detection and tracking of eye-based features improvement in recent years, data still remains a noisy. In the case of blink based metrics it is particularly problematic because a non-detected eye may be interpreted as an eyelid closure. Glasses' lens can hinder the pupil detection. In real world conditions, sunglasses or body postures not facing the camera nullify any eye-metric based system.

Behaviour based metrics are a promising source for information for detecting drowsiness due to a set of behaviours associated with drowsiness. One reason for this behaviour change is the driver's perception of its condition and by changing the behaviour to counter the fatigue progression. Other common goal is to change the posture to a more confortable positions. These type of behaviour can be classified as: 1) postural adjustments, 2) verbal exchanges, 3) ludic activities, and 4) self-centered [35]. One of major advantage of these metrics is that it resembles the way a passenger looking to the driver would infer the fatigue. Because of this intuitive nature it allows synthesizing a rule-based system easily, for instance fuzzy based systems [30].

The performance of such behaviour activities is person dependent, so when people perceive themselves fatigued they may do several of these activities. This also implies that even if the driver doesn't perform such activities s/he may be fatigue, so behaviour-based metrics should not be used alone since they are not a sufficient for detection. Another limitation is that each specific cue requires a specific detection algorithm, which considerably limits the detection capability due to practical reasons, and restricts the cues to a set of generic ones.

4. Conclusions and discussion

HAD concept tries to automate as much as possible the driving task, this way freeing the driver to engage in other tasks. Yet, the human driver still retains the responsibility to resume the vehicle control in situation where the automation cannot handle. The TOR process contains many challenges that must be address in order to achieve our goal of allowing the driver to engage in other tasks and effectively support him to resume control in a safe manner.

One way to compromise the safety of a TOR process is to assume the driver is in a good status every time the a TOR initiates. This process should not be set with fixed time buffers [36], but adjust the time buffer to the driver state. In practice, this is an application of the knowledge produced in the context of manual driver, for instance fatigued drivers have higher reaction times.

DSMS have been relying mainly on eye based metrics and driving performance. Eye metrics have more recently enjoyed the benefit of better technology, which has translated into more reliable measurements. In this sense it is expectable that they remain with similar role for this new generation.

Driving performance data absence is the major change in this field, providing reliable data even in situations where eye-tracking data was not available. This data does not totally disappear because it can still be useful for during the TOR process, for instance to detect if the driver is capable of handling the transition. Without these emergency TOR use cases, the more common use case is to not have any driving performance available.

We expect that this can create an opportunity for other advancing other type of data for accessing driver state. For distraction detection, a possible alternative could be monitoring the body posture. The freedom allowed in HAD can be used for less conventional body postures that could, along with head rotation a indicator if the driver is deviating from what a normative driving posture would be.

Fatigue countering behaviour has received yet little attention in DSMS. There is evidence that drivers under fatigue behave differently either by adjusting their body posture or by trying to interact with themselves (scratching face, covering mouth, rubbing eyes…).

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